Including mark–recapture data into a spatial age-structured model: walleye pollock (*Theragra chalcogramma*) in the eastern Bering Sea

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Abstract: Integrated assessment models used to evaluate fish stocks are becoming increasingly complex, with some capable of incorporating spatial considerations. Such a model has been developed to estimate movement of walleye pollock (*Theragra chalcogramma*) between the northwestern and southeastern eastern Bering Sea. In this study, we investigate the feasibility of estimating movement using spatially disaggregated data supplemented by tagging data. Monte Carlo simulation was used to test accuracy and variability of parameter estimation in model scenarios with and without tagging information. Total biomass estimates for models with and without tagging data were unbiased, but uncertainty was smaller when tagging data were available. Uncertainty was also reduced in regional biomass and movement parameters when including tagging data. Our findings indicate that tagging information would be important to provide reliable spatially explicit fisheries management advice for eastern Bering Sea pollock.

Résumé : Les modèles intégrés d'estimation utilisés pour évaluer les stocks de poissons deviennent de plus en plus complexes, certains étant capables d'incorporer des considérations spatiales. Un tel modèle a été mis au point pour estimer les déplacements de la goberge d'Alaska (*Theragra chalcogramma*) entre le nord-ouest et le sud-est de la mer de Béring orientale. Dans notre étude, nous examinons la faisabilité d'estimer les déplacements en utilisant des données spatialement désagrégées, additionnées de données de marquage. Une simulation de Monte Carlo sert à tester l'exactitude et la variabilité de l'estimation des paramètres dans les scénarios du modèle avec et sans données de marquage. Les estimations de la biomasse totale dans les modèles avec et sans marquage sont non biaisées, mais l'incertitude est plus petite quand des données de marquage sont disponibles. L'incertitude est aussi réduite dans les paramètres de biomasse régionale et de déplacement lorsqu'on inclut les données de marquage. Nos résultats indiquent que les données de marquage pourraient être importantes lorsqu'on veut fournir des avis de gestion fiables et spatialement explicites sur la goberge de la mer de Béring.

[Traduit par la Rédaction]

Introduction

Because the true mechanisms and processes underlying the natural world are unknown, researchers describe the system using models based on available observations. These data sets typically lack the contrast needed to estimate more complex parameterizations because parameters can become confounded due to the statistical models employed. For example, natural mortality parameters are often confounded with movement parameters in spatial models, in which case, tagging data have been proposed as a way to address parameter confounding (Anganuzzi 1996).

One of the most powerful tools available to test assessment models in fisheries science is simulation (Hilborn and Mangel 1997). Monte Carlo simulation has been used to determine model robustness from incorrectly specifying the error structure or parameter structure (e.g., Fu and Quinn 2000).

By using simulated data, the researcher knows the true parameter values and can then evaluate model performance (Hilborn and Mangel 1997). Through realistic simulation that includes aspects of random variability in dynamics and observation, it is important to investigate the biases, effectiveness, and impacts on management procedures of new stock assessment methods (Hilborn and Walters 1992; Maunder 2001). This study presents an application of simulation-estimation tests for a relatively complex spatially explicit movement model.

Changes to a fish population structure over space or time can affect fish stock assessment estimates of potential fishery yields and mortality. Assuming that there is no movement in a fish population when movement actually occurs can lead to a loss in potential harvests (Tuck and Possingham 1994). Conversely, assuming movement when populations are relatively stationary over space or time can lead to depletion im-

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Table 1. Years of spatially disaggregated data sources available for the northwestern (NW) and southeastern (SE) regions of the eastern Bering Sea pollock. Total yield included all years (1977 to 2005).

Region	Season	Bottom-trawl survey abundance	Echo-integrated trawl survey abundance	Fishery (catch-at-age and yield)
NW	A			1977–2005 (missing 1988–1990, 1997)
	B	1982–2004	1994, 1996, 1997, 1999, 2000, 2002	1977–2005 (missing 1988–1990)
SE	A			1977–2005 (missing 1988–1990)
	B	1982–2004	1994, 1996, 1997, 1999, 2000, 2002	1977–2005 (missing 1988–1990)

Note: The "A" season fishery occurs subsequent to the start of the year from January to June with half-year natural mortality; the "B" season fishery is subsequent to the first regional movement and occurs from July to December with half-year natural mortality.

balances with fishing (Hilborn and Walters 1992). Incorporation of movement in fish stock assessment analysis is rare because of the lack of tagging information and added model complexity (Quinn and Deriso 1999). Consequently, spatial assessment models are uncommon in fishery management settings, but there have been some promising developments.

An age-structured movement model has been developed for eastern Bering Sea (EBS) walleye pollock (*Theragra chalcogramma*, hereafter referred to as pollock) that estimates movement based on spatially disaggregated survey and fishery data (Miller et al. 2008). A method for including tagging data into assessment models was provided by Maunder (2001). In this model, the tagged fish follow the same population dynamics of the entire population and are essentially modeled as a subset of the entire population within the assessment model. Other spatial models that include tagging data are those of Punt et al. (2000) and Hanselman et al. (2007). The first is a spatially explicit model for school shark (*Galeorhinus galeus*) off southern Australia that includes tagging data. The latter is a size-based migration model designed for the migratory Alaska sablefish (*Anaplopoma fimbria*) and uses mark–recapture data sets that began in 1979 (Heifetz and Fujioka 1991). Also, a size-structured model that includes mark–recapture information for South Australian rock lobster (*Jasus edwardsii*) has been developed (McGarvy et al. 2010) and is used for management advice.

The groundfish fishery for pollock in the EBS is one of the world's largest, and catch limits are managed by seasons. During spring and summer in the EBS, pollock are thought to migrate to feeding areas, and during the late fall and early winter, they migrate to spawning areas. Pollock distribution with respect to temperature obtained from EBS surveys shows that feeding migrations tend to follow a northward and shoreward movement, the extent of which increases with increasing size of pollock (Kotwicki et al. 2005). Currently, there is no movement information from a large-scale EBS pollock mark–recapture study, but feasibility studies for tagging of pollock have shown the potential for sufficient sample size and survival rates (Natural Resources Consultants, Inc., and Northwest Marine Technology, Inc. 1996; Miller 2007; Winter et al. 2007).

Using disaggregated survey and fishery catch data, age-specific pollock movement between the northwestern (NW) and southeastern (SE) EBS was estimated using an age-structured assessment movement model (ASM; Miller et al. 2008). This model differs from the present EBS pollock stock assessment that is based on a standard age-structured stock assessment model (Ianelli et al. 2009) and does not estimate movement. Under moderate assumptions for spatial structure (the number of regions in which movement was estimated),

reasonable estimates of most population and movement parameters could be obtained. However, some parameter estimates were highly uncertain and correlated, and the analysis lacked a formal evaluation of accuracy and precision. In the current study, the utility of additional information from a hypothetical mark–recapture program is examined and compared with the ASM model constructed by Miller et al. (2008). We do not consider interpopulation movement, rather that the pollock "stock" exhibits intrapopulation movement between the two regions in the EBS. The ability to reliably estimate movement parameters was tested using Monte Carlo simulation (Hilborn and Mangel 1997). Given specified spatial and seasonal population characteristics, we investigated the bias and variability in parameters and population estimates across a variety of scenarios, including the addition of tagging data. The goals were to determine (*i*) the benefits of having tagging data sets for the ASM model, (*ii*) the sensitivity of results to tag-release protocols (e.g., season and area of releases), and (*iii*) the magnitude of bias and variability in population parameter estimates without tagging data.

Materials and methods

In this study the ASM model developed by Miller et al. (2008) was used as the operating model. Estimates based on the original data fit with the ASM model formed the "true" state of nature from which data were generated (with specified errors) for subsequent fitting by the estimation models (Table 1). The two regions considered for the EBS in Miller at al. (2008) were divided into NW and SE by the 170°W meridian (Fig. 1). The data sets used in the ASM model are described in Miller et al. (2008). The Aleutian Islands and the Gulf of Alaska were not included in the analysis.

As the primary focus of this study was to evaluate the effect of tagging data on ASM model estimates, tagging data by region and season were also generated and applied to an integrated tagging and catch-at-age analysis (ITCAAN) estimation model (Maunder 2001). Results from the simulation analyses were compared through bias and variability in the movement parameters and biomass estimates. The simulation procedure was executed with customized code in R language (R Development Core Team 2008) that integrated R with AD model builder (ADMB; Fournier 1996). The ASM and ITCAAN estimating models were written using ADMB, and the operating model and simulation–estimation loops were written using R. For each variance scenario, 1000 operating model simulations were evaluated; the number of simulations was selected to obtain robust estimates of variance (e.g., Efron and Tibshirani 1993). Further, the ASM and ITCAAN models in each simulation used the same generated data

Fig. 1. Map showing the northwestern (NW) and southeastern (SE) regions of the eastern Bering Sea considered in the spatial modeling of walleye pollock.
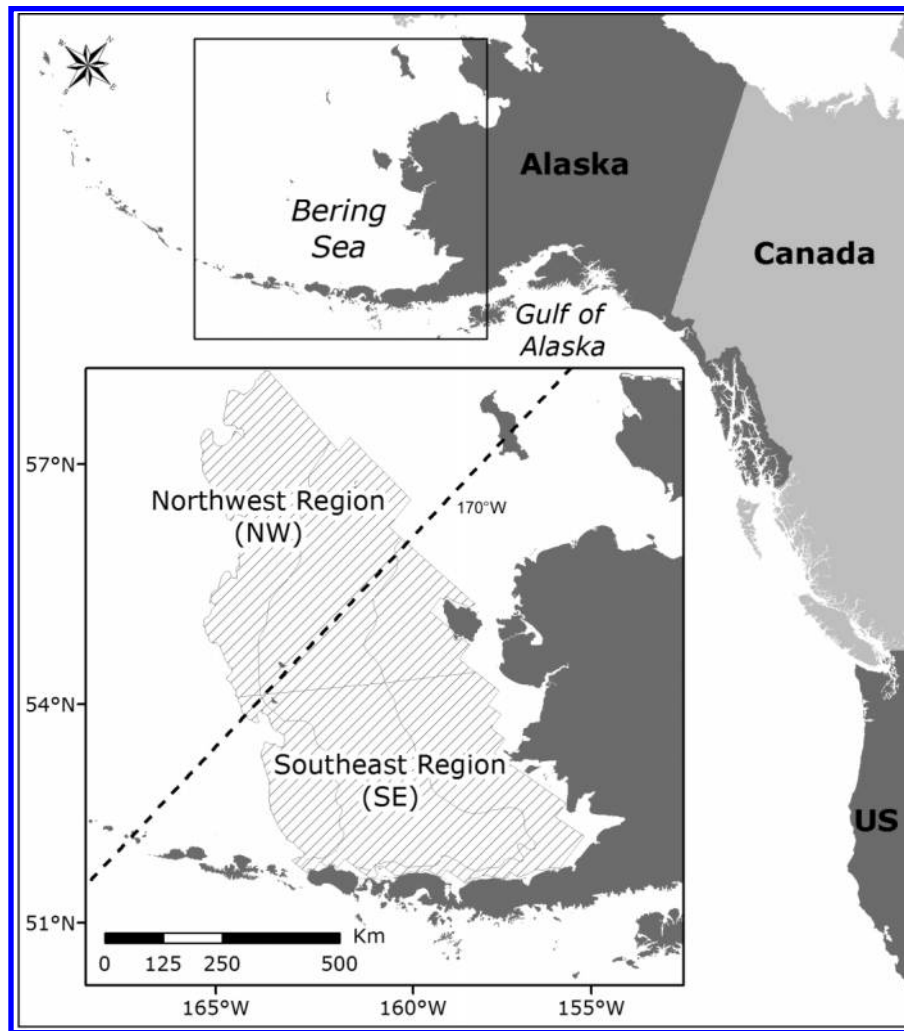
except the generated tag-recovery data because the ASM model does not fit tag-recovery data.

Operating model

In Miller et al. (2008), the population dynamics of EBS pollock was modeled with a discrete-time and region-specific ASM model (Quinn and Deriso 1999; Maunder 2001). The generalized dynamics of pollock in region r at age a in year y at the start of the year in the ASM model can be formulated as the sequence of spatial (regions NW, SE) and temporal (seasons A and B) events shown (Fig. 2). Pollock spawn in the winter, and this time period is used in the ASM model as the start of the modeling year (1 January). The A season fishery occurs subsequent to the start of the year from January to June. After the A season, the first regional movement between the NW and SE takes place to reflect movement of pollock from the spawning to summer feeding grounds. During this time, half of the year's natural mortality was applied to the population. The B season fishery is subsequent to the first regional movement and occurs from July to December. After the B season fishery, the second regional movement was modeled to reflect movement back to spawning grounds in the fall, and the second half of the year's natural mortality

is applied. Note that when movement occurs, it is not the entire population moving from region to region, rather a proportion of the population that moves as determined by the probability of movement estimated by movement parameters. The population after the A fishing season at age a in year y was the first step (step 1) in the yearly population dynamics equation:

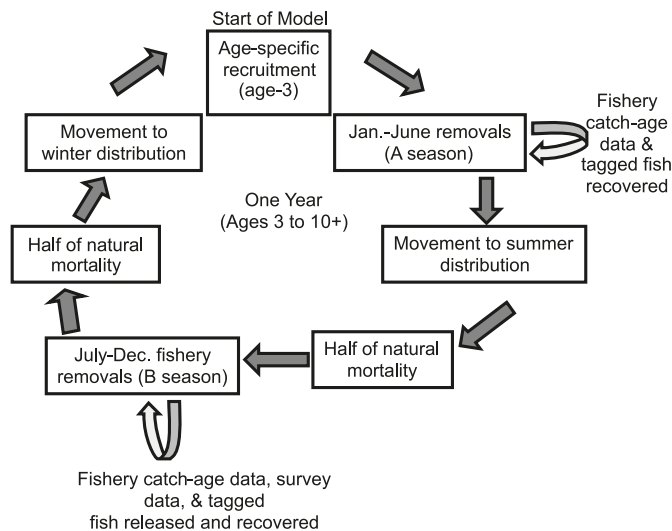$$(1) \qquad {}^1_r N_{a,y} = {}_r N_{a,y} e^{-{}_r F_{a,y,A}}$$

Movement from the winter spawning grounds to summer feeding grounds (step 2), with half-year natural mortality, was modeled as

$$(2) \qquad {}^2_r N_{a,y} = ({}^1_r N_{a,y} \theta_{r \to r, A} + {}^1_{r'} N_{a,y} \theta_{r' \to r, A}) e^{-M/2}$$

in which the abundance in region r is the sum of the numbers of fish that stay in region r ($r \to r$) and the numbers that leave region r' for region r ($r' \to r$). The B season fishing mortality was applied to the population in step 3:

$$(3) \qquad {}^3_r N_{a,y} = {}^2_r N_{a,y} e^{-{}_r F_{a,y,B}}$$

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Fig. 2. Depiction of the two-area, two-season model for pollock in the eastern Bering Sea showing the processes affecting the population. Figure modified from Miller et al. (2008).

Fig. 3. Movement parameter estimates, by age, modified from Miller et al. (2008). $\theta_{NW \rightarrow NW,A}$ and $\theta_{NW \rightarrow NW,B}$, the probability that age 3 fish stayed in the NW after seasons A and B, respectively; $\theta_{SE \rightarrow SE,A}$ and $\theta_{SE \rightarrow SE,B}$, the probability that fish of all ages stayed in the SE after seasons A and B, respectively.

After the B fishing season movement from the summer feeding grounds back to the spawning grounds, the final step in the yearly population dynamics (step 4) was estimated by

$$(4) \qquad _r^4N_{a,y} = \left(_r^3N_{a,y}\theta_{r \rightarrow r,B} +_{r'}^3N_{a,y}\theta_{r' \rightarrow r,B}\right)e^{-M/2}$$

which becomes the population abundance at the beginning of the next year. The prime notation is used to describe the alternate region, that is, if r = NW then r' = SE. In these equations, F represents fishing mortalities for the A and B seasons, M is natural mortality, and θ is the probability of movement after fishing seasons A or B from region r to region r', which may also be a function of age.

Pollock are thought to move seasonally and with a general ontogenetic pattern that shifts southeastward with increasing age (Buckley et al. 2001). For the NW region, the operating model was conditioned such that the probability of movement from the NW to SE was an increasing linear function of age. For convenience, the modeling of movement was parameterized in terms of probability of staying in the same region (1 – probability of movement). Based on available knowledge, the probability that age 3 fish stayed in the NW after the A season was $\theta_{NW \rightarrow NW,A}$ = 99% and the probability after the B season was $\theta_{NW \rightarrow NW,B}$ = 75%. These amounts were multiplied by 80% for each successive age class for movement after the A fishing season and by 90% for the movement after the B fishing season (Miller et al. 2008). For the SE EBS, available knowledge suggests that the probability of staying in the SE region was constant for all ages, equal to $\theta_{SE \rightarrow SE,A}$ = 30% after the A season and $\theta_{SE \rightarrow SE,B}$ = 70% after the B season (Miller et al. 2008). These four parameters were estimated in the estimation model. The corresponding age-specific movement rates are shown (Fig. 3).

Data generation

Data were simulated by generating random variability about the expected values from the operating model and fitting the generated data with the estimation model structures. In the simulation analysis, a total of 13 data sets (Table 2)
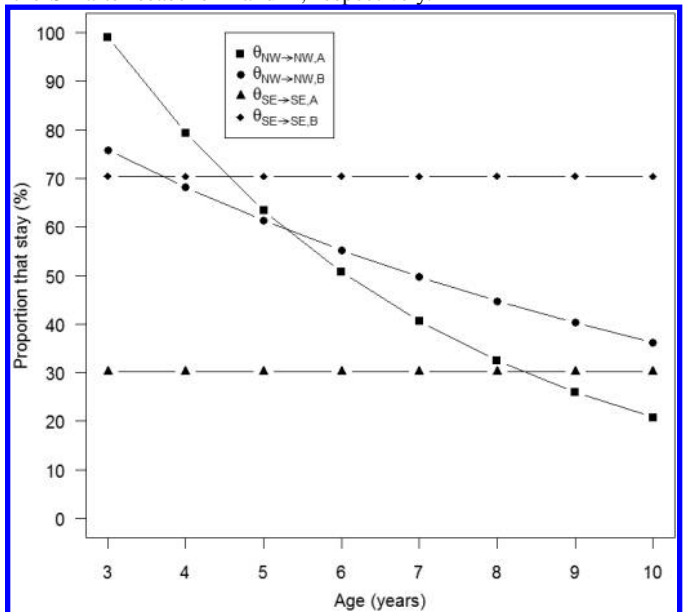
were generated and employed in the ASM model structure and 17 in the ITCAAN model structure. The four additional data sets in the ITCAAN model were tag-return data from the two regions and two fishery seasons (Table 3). Because the lognormal distribution was used in the ASM model fit by Miller et al. (2008), simulated data were structured to follow a lognormal distribution to provide a direct comparison with the prior study:

$$(5) \qquad x_i = \bar{x}e^{\left(\varepsilon_i - \frac{\sigma^2}{2}\right)}, \quad \varepsilon_i \sim N(0, \sigma)$$

in which $\bar{x}$ is the "true" value from an area and year, ε_i is the randomly generated normal deviation for simulation i, and σ is the prespecified standard deviation. The values for σ in the estimation model were set to a range of different values relative to the "true" operating model values (Tables 2 and 3).

Because tagging information was the key focus in this study, "observed" tag-recovery data were constructed in the operating model by a simulated tagging program. In this program, there were annual releases of tags into the marked population in both regions for all ages 3 to 10+ during the summer surveys. To evaluate the effect of the number of years that tag release and recovery were conducted, two cases were considered. In the first case (case I), tagged fish were released in each year from 2000 to 2002. In the second case (case II), tagged fish were released in each year from 1995 to 2002. Recoveries for both cases start in the first year of tagging and continue through 2004. We refer to a spatial model with both regular assessment data and mark–recapture data as an integrated tagging and catch-at-age analysis (ITCAAN) model after Maunder (2001).

In the ITCAAN model, the tagged and the total population (including both tagged and untagged fish) were modeled simultaneously with the same dynamics and parameter values

Table 2. Input values for σ (used in the lognormal distribution) relative to different spatially disaggregated data sources.

Data sources	Region	Season	σ
Fishery yield	NW	A	0.05
		B	0.05
	SE	A	0.05
		B	0.05
Total fishery yield	na	na	0.025
Fishery catch-at-age	NW	A	0.3
		B	0.2
	SE	A	0.2
		B	0.2
Bottom trawl survey	NW	na	0.2
	SE	na	0.2
Echo-integrated trawl survey	NW	na	0.2
	SE	na	0.2

Note: In the Region and Season columns, "na" means not applicable; NW and SE, northwestern and southeastern regions of the eastern Bering Sea, respectively. See Table 1 or text for explanation of seasons A and B.

Table 3. Standard deviations considered in the two uncertainty scenarios (*a* and *b*) for tag-recovery data.

Region	Season	Scenario *a*	*b*
NW	A	0.05	0.7
	B	0.05	0.2
SE	A	0.05	0.1
	B	0.05	0.1

Note: NW and SE, northwestern and southeastern regions of the eastern Bering Sea, respectively. See Table 1 or text for explanation of seasons A and B.

(e.g., Maunder 2001), except that the initial tagged populations at the start of the mark–recapture program were the numbers of releases by regions and ages. It was assumed that the pollock would be implanted with magnetically detectable coded wire tags (CWT) by a research vessel in the summer during the bottom trawl survey (BTS) such that fish in different regions would receive different tags. In this study, we did not consider tag-induced mortality, as an actual tagging program has not been implemented for pollock and it would be difficult to presume what tag-induced mortality would be. It was further assumed that fish would be recovered by the commercial fishery in either fishery season A or B. There are three fishing sectors in the EBS: (1) fishing vessels with shoreside processors (50% of total acceptable catch (TAC)), (2) fishing vessels with offshore mothership processors (10% of TAC), and (3) vessels that both harvest and process their catch offshore (40% of TAC). Only the feasibility of installing electronic CWT detectors in shoreside processing plants has been determined (National Research Council 1996). Therefore, only the proportion of the catch typically caught by the fishing vessels with shoreside processors was considered in the tag-recovery process.

The number of recoveries ($^{r}R_{a,y,s}$) at age a in year y from region r and season s was generated by

(6) $$^{r}R_{a,y,s} = {}^{r}p\,{}^{r}T_{a,y,s}\left(1 - \mathrm{e}^{-{}^{r}F_{a,y,s}}\right)$$

in which $^{r}T_{a,y,s}$ is the number of marked individuals at age a in year y from region r and season s after one-half year of natural mortality, F is the fishing mortality, and ^{r}p is the proportion of the total catch delivered to shoreside processors from region r. For simplicity, this proportion was treated as constant over time, which is reasonable from examination of catch data. Recoveries are a function of the exploitation fraction of the fishery; incidental recoveries from survey effort were omitted as total catch during a survey is very low. The proportion of total catch from region r (^{r}p) delivered to shoreside processors, derived from observed regional landings from 2003–2005, was set at 7% from the NW region and at 39% from the SE region (Miller 2007). As an actual tagging program has not been implemented for pollock, in

this simulation study, it was assumed that there was no tag loss or tag-induced mortality for fish that were tagged with CWTs and that the total catch delivered to shoreside processors was examined for tags with a detection rate of 100%. Thus, to simplify, non-reporting rate, tag-induced mortality, and tag loss were considered negligible (e.g., Haist 1998).

Two methods of releasing tags during the survey were examined in the simulation analysis. In the first method, tags were released evenly across the NW and SE regions. In this case, 5000 tags were released in the NW and 5000 in the SE during the BTS survey. In the second method, tags were released proportionally to the BTS survey catch: 67% (6700) of the tags were released in the NW region and 33% (3300) were released in the SE during the survey. In both cases, it was assumed that the ages at the time of tagging were known, the tags were distributed uniformly across age classes, and the tagged fish mixed completely in the population with untagged fish. Fitting the ITCAAN model to even tagging is denoted by ITCAAN$_{E}$, and fitting to proportional tagging is denoted ITCAAN$_{P}$. The two cases for the number of years for which tags were released for each tagging method were denoted as (even tagging, for example) ITCAAN$_{E,I}$ for case I and ITCAAN$_{E,II}$ for case II.

Two uncertainty scenarios for the tag-recovery data were used in the simulation (Table 3). In the first scenario (*a*), the standard deviation for tag recoveries was set at 0.05 to represent a case in which the uncertainty in tag returns was low. The second scenario (*b*) used standard deviations that were proportional to the inverse of the number of tag recoveries. This scenario was selected to evaluate uncertainty that is related to the sample size of tag recoveries obtained.

Estimation models

In both the ASM and ITCAAN models, parameter estimates were obtained using an objective function that represented the negative log likelihood of normalized residuals. The objective function consisted of 13 data set sources for the ASM model (Table 2; Miller et al. 2008). For the ITCAAN model, there were the 13 data set sources fitted in the ASM, with an additional four data sets for tag recoveries by fishing season and region (Table 3). The weighting terms, or equivalently the data set standard deviations, were derived from either the 2009 stock assessment report (Ianelli et al. 2009) or were assigned a value consistent with available knowledge (Table 2).

In the ITCAAN estimation model, the tag-release data were directly input into the model, because this information would be known. The tag recovery data sets were fit in the

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Fig. 4. Total, NW, and SE biomass in 2005 estimated by the ASM and ITCAAN models. Tag-recovery data uncertainty scenario *a* is shown in the left panel, and scenario *b* is shown in the right panel. The box represents the interquartile range from the estimation models, the whiskers (broken vertical lines) represent the 95% confidence interval, and values outside the 95% confidence intervals are shown with open circles. For the models, P and E refer to proportional and even tagging, respectively, and I and II refer to case I and case II release dates, respectively.
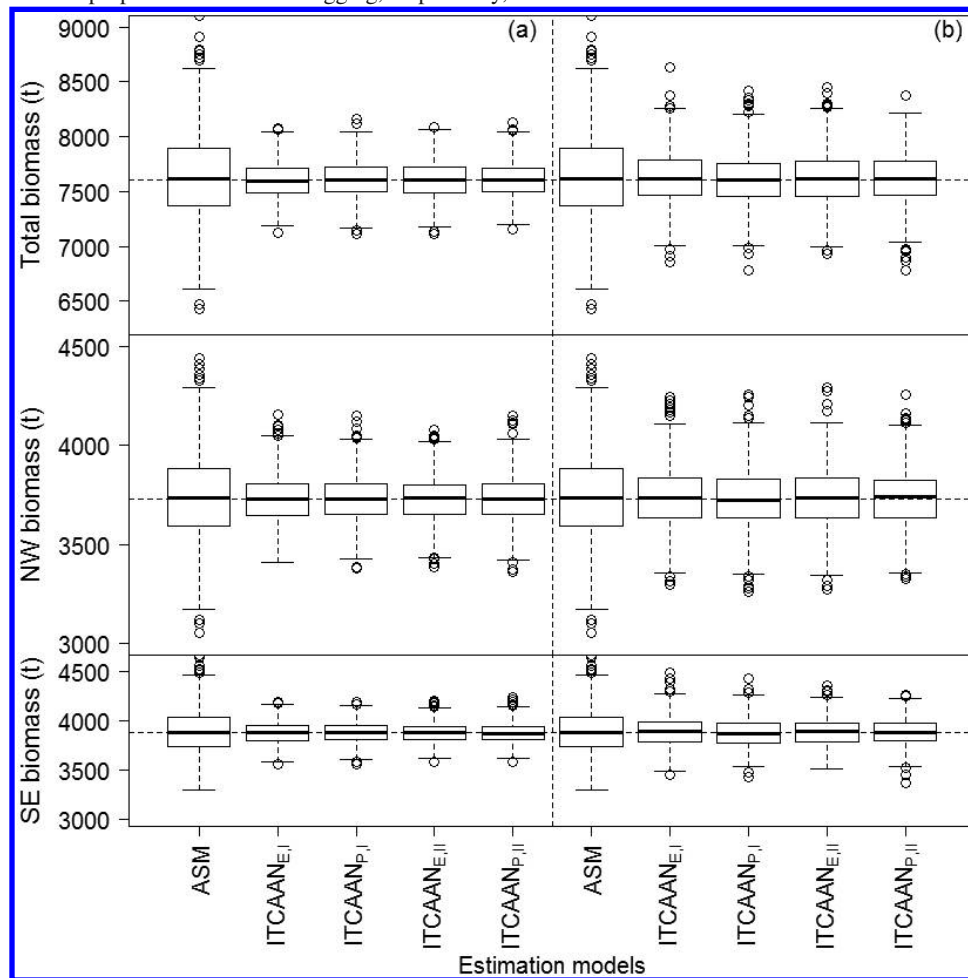
estimation model after being estimated following eq. 6 with a lognormal likelihood. We considered only region-specific tags rather than year- and region-specific tags; more sophisticated treatments of tagging data would potentially improve the ITCAAN model but are beyond the scope of this study. The lognormal distribution rather than discrete distributions (i.e., Poisson, multinomial) was used to provide more direct comparison with Miller et al. (2008), as the lognormal likelihood was used in that study. Further analysis is being conducted that uses discrete distributions to generate tagging data sets. In each tag-recovery data set uncertainty scenario, the standard deviations used in data simulation were subsequently used in the objective function as the likelihood variance to fit the generated data sets. We did not consider misspecification of variance in the estimation model.

For presentation, we focused on estimates of movement parameters and total and regional biomass in the results. For total and regional biomass, the results focus on the estimate in the last year of the model, as this is the crucial year from which forecasts and harvest recommendations are made to managers. Estimated asymptotic approximations to the standard deviations of the biomass and movement parameters were also provided. Box plots of these key parameters were used

for presentation, the box represents the interquartile range from the estimation models and the whiskers (vertical broken lines) represent the 95% confidence interval. Bias was considered significant if the value from the operating model was outside the 95% confidence intervals.

Results

Overall, the variability in the estimates of total and regional biomass in the last year was reduced when tagging data sets were integrated into the stock assessment model (Fig. 4). Estimated total and regional biomass for both the ASM and ITCAAN models were not biased (Fig. 4). The estimated standard deviations in total and regional biomass from ADMB were smaller for the tag-recovery data set uncertainty scenario *a* as compared with scenario *b* for the ITCAAN models, but the estimated standard deviations from the ASM model were larger than either tag-recovery data set uncertainty scenario for the ITCAAN models (Fig. 5). Results were similar when tagging evenly between regions or proportionally to the BTS survey when considering the estimated standard deviations in total and regional biomass in the last year of the model (Fig. 5). Further, the estimated standard

Fig. 5. Standard deviations (SD) in total, NW, and SE biomass in 2005 estimated with ADMB for the ASM and ITCAAN models. Tag-recovery data uncertainty scenario *a* is shown in the left panel, and scenario *b* is shown in the right panel. The box represents the interquartile range from the estimation models, the whiskers (broken vertical lines) represent the 95% confidence interval, and values outside the 95% confidence intervals are shown with open circles. See Fig. 3 or text for movement parameter details and Fig. 4 or text for model details.
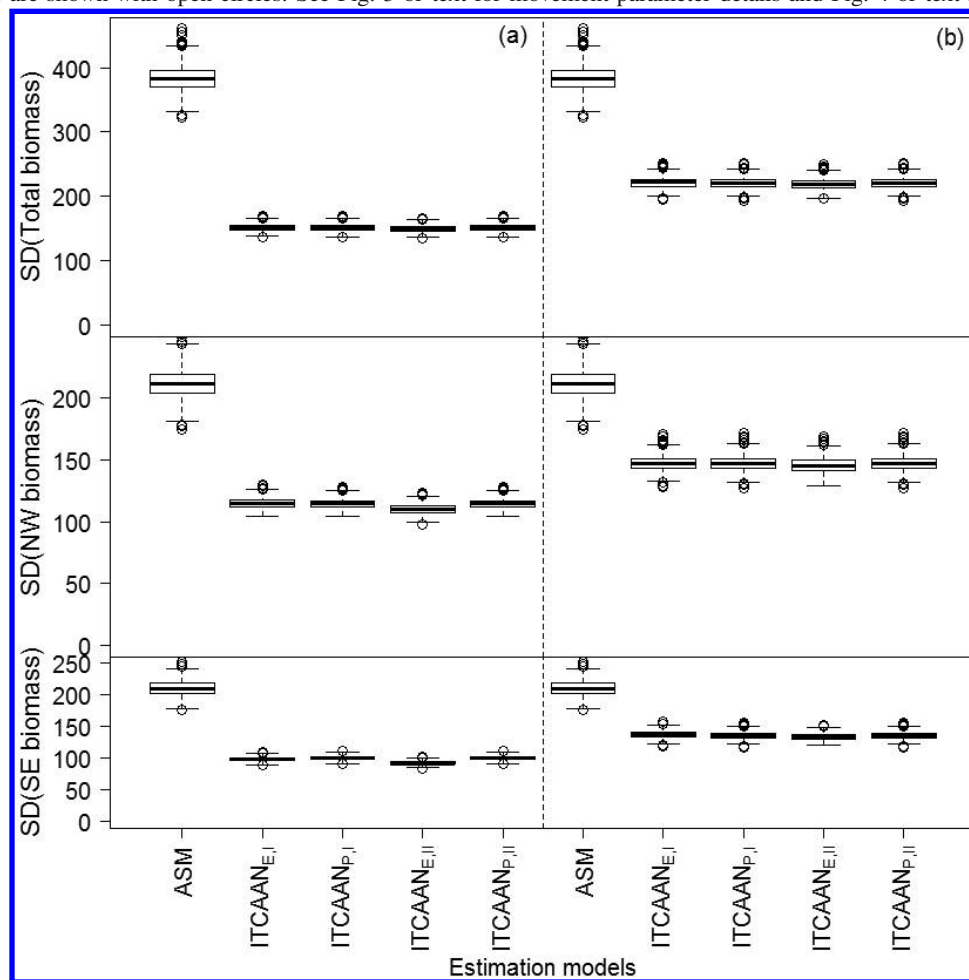
deviations in total and regional biomass were similar regardless of the length of the tag data set time series (Fig. 5).

Parameter estimates for regional and seasonal movement were unbiased for both the ASM and ITCAAN models (Fig. 6). The estimated standard deviations in the movement parameter estimate for the NW region after season A ($\theta_{\mathrm{NW}\rightarrow\mathrm{NW},A}$) were similar for both the ASM and ITCAAN models (Fig. 7). Even though reduction in the estimated standard deviations was small, for all other movement parameters, the estimated standard deviations from ADMB were decreased in the ITCAAN models compared with the ASM model (Fig. 7). The largest differences in estimated standard deviations for movement parameters between the ASM and ITCAAN models occurred for tag-recovery data uncertainty scenario *a* compared with scenario *b*. In scenario *b*, the estimated standard deviations in movement parameters from the ITCAAN models were only slightly lower than from the ASM model, but the general patterns were similar to results from scenario *a* (Fig. 7). When uncertainty was low in the tag-return data in scenario *a* and tags were released evenly between regions, the estimated standard deviations of movement parameters were smaller when the time series of tag-recovery data were longer (case II compared with case I). When tag-

ging proportionally to the BTS survey, the estimated standard deviations in movement parameters were similar regardless of the length of the tag-recovery data (Fig. 7). Comparing between tag-release methods, in tag-recovery data set uncertainty scenario *a*, the estimated standard deviations of movement parameters were smaller when tagging evenly across regions as compared with tagging proportionally to the BTS survey; the same resulted for tag-recovery data uncertainty scenario *b*, but the differences were not as notable (Fig. 7).

Discussion

The quality and quantity of data and the soundness of assumptions all directly affect the accuracy of models and their predictions (National Research Council 1998). Both the ASM and ITCAAN models resulted in significantly unbiased estimates of parameters and population biomass. This is a consequence of the operating and estimation models being the same, but it also shows that there was apparently no appreciable parameter confounding even in the absence of tagging data. Our simulation study showed that an advantage of including tagging data sets into a spatially

Fig. 6. Estimated movement parameters from the ASM and ITCAAN models. Tag-recovery data uncertainty scenario *a* is shown in the left panel, and scenario *b* is shown in the right panel. The box represents the interquartile range from the estimation models, the whiskers (broken vertical lines) represent the 95% confidence interval, and values outside the 95% confidence intervals are shown with open circles. See Fig. 3 or text for movement parameter details and Fig. 4 or text for model details.
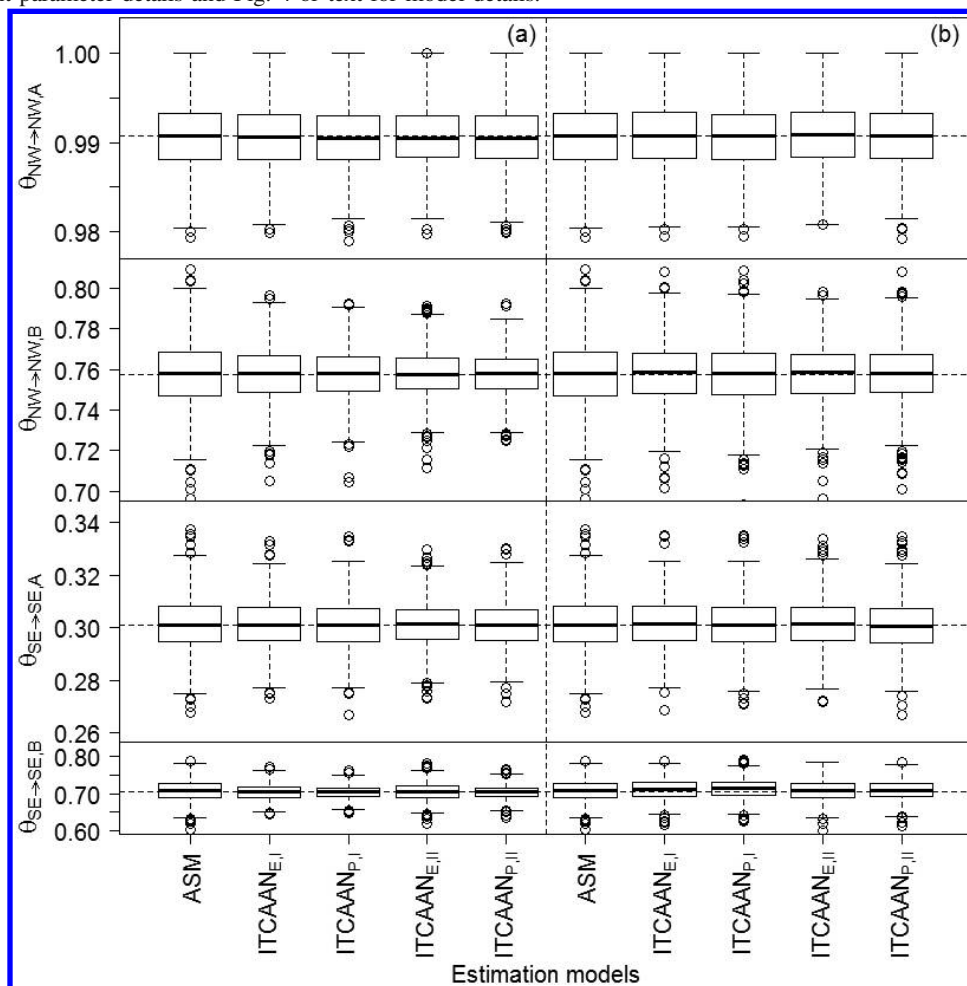
explicit age-structured stock assessment model is primarily reduced variability in population biomass estimates and movement parameters. Even with a small-scale tagging study, there was reduced variability in estimated total and regional biomass with the addition of tagging data. Thus, even if there is a large amount of uncertainty in observed data, the inclusion of tagging data will reduce the uncertainty in stock assessment estimates of biomass that are subsequently used for fishery management.

Variability was generally smaller in the movement parameter estimates when tagging data were included into the stock assessment model. When the movement parameter was near one (99%), however, variability was not affected, as shown with the movement parameter estimated after fishing season A in the NW region (which is actually the probability of staying in the NW region). For all other movement parameters, variability decreased when tagging data was used. We found that the number of years available for tag-return data also influenced variability in the movement parameters. The differences in movement parameter variability when considering the length of tag-return data were more evident when uncertainty was low in the tag-recovery data. When uncertainty in the tag-recovery data was larger, there was not a substan-

tial improvement in movement parameter variability. Thus, the variability in the movement parameters decreased as the time series of tag data increased, but the magnitude of improvement in movement parameter variability depended on the uncertainty in the tag-recovery data and the tag-release protocol.

Releasing tags evenly between regions provided the largest reduction in movement parameter variability. When tagging proportionally to the BTS survey catch, we found that the variability in movement parameters was not largely affected by the number of years for which tag-recovery data were available. However, variability in movement parameters was reduced when tagging evenly between regions as the number of years for which tagging data sets were available increased. Thus, we found that it is better to release tags evenly among regions rather than proportionally to abundance in this example. However, in this study, we considered the simplified case in which complete mixing of tagged and nontagged fish occurs immediately after the tags were released. Perhaps, the spectrum of movement scenarios was too limited in this simulation; it may be that with alternative movement hypotheses such as random yearly movement, tagging proportionally may result in less uncertainty than tagging evenly. Also, the

Fig. 7. Standard deviations (SD) in movement parameters estimated by ADMB for the ASM and ITCAAN models. Tag-recovery data uncertainty scenario *a* is shown in the left panel, and scenario *b* is shown in the right panel. The box represents the interquartile range from the estimation models, the whiskers (broken vertical lines) represent the 95% confidence interval, and values outside the 95% confidence intervals are shown with open circles. See Fig. 3 or text for movement parameter details and Fig. 4 or text for model details.
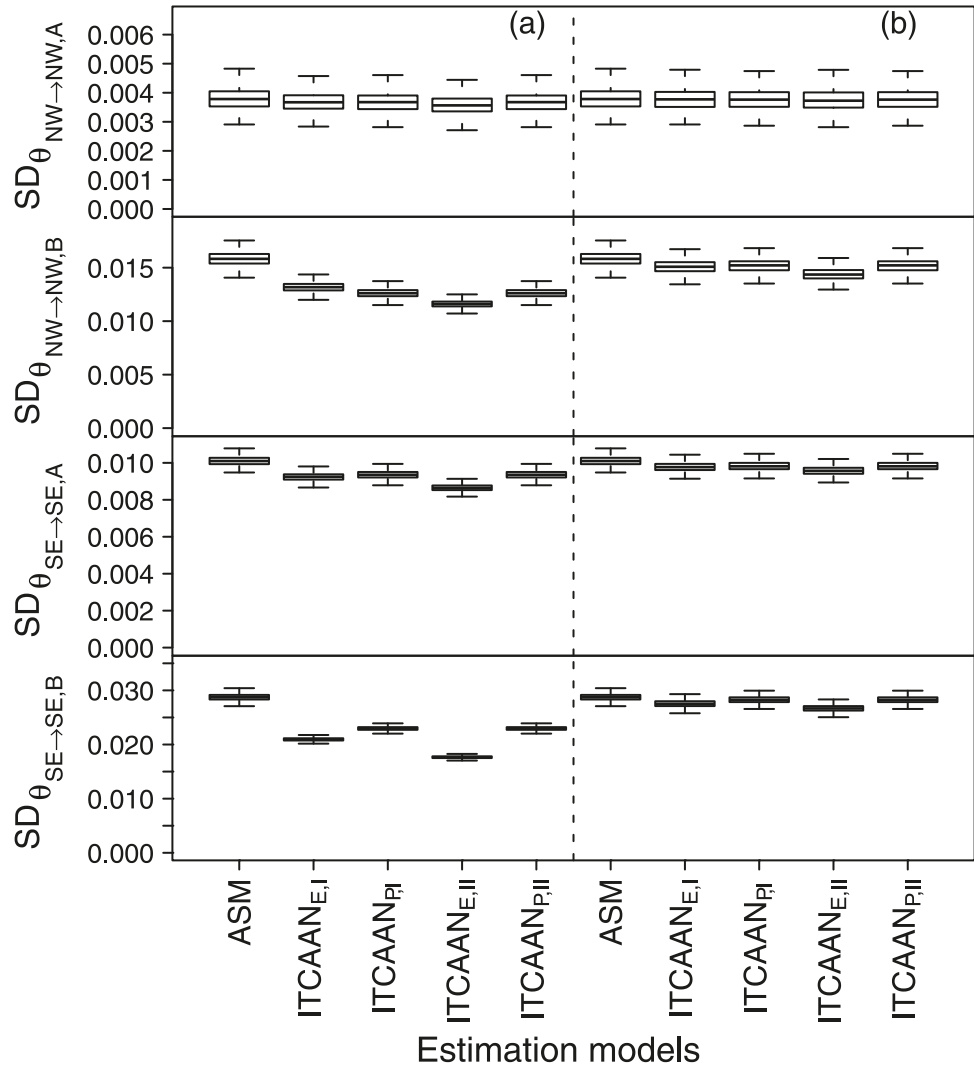
amount of mixing between tagged and untagged fish could identify differences between tag-release protocols, a topic that requires further study. Our model is ideally suited to evaluate alternative experimental designs and protocols.

Pollock migration patterns could vary in the future from historical patterns due to climate change forcing (e.g., Mueter and Litzow 2008). Temperature changes in the Bering Sea can affect pollock distribution between the US and Russian Exclusive Economic Zones and the availability of this species to each fishery. Temperature changes can also affect the timing of pollock migration and the proportion of the stock within the standard EBS survey area when the survey is conducted (Kotwicki et al. 2005). Because the EBS pollock stock migrates further north as Bering Sea temperatures rise, these pollock may be missed in the EBS survey estimates, caught by the Russian fishery, and create management complications when determining the EBS total acceptable biological catch (Ianelli et al. 2001). In this simulation, movement was assumed constant across years. However, because of reduced uncertainty in total and regional biomass estimates when comparing the ASM and ITCAAN models, we hypothesize that tagging data would provide more accurate and precise estimates from stock assessment models when movement is stochastic, a hypothesis that will be tested in future research. If this is the case with tagging data, management decisions would be made with less uncertainty, less likelihood of over-harvesting, and potentially higher sustained yields.

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